Efficient Hybrid Model for Intrusion Detection Systems

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Abstract: This paper proposes a new hybrid ML model that relies on K-Means clustering and the Variational Bayesian Gaussian Mixture models to efficiently detect and classify unknown network attacks. The proposed model first classifies the input data into various clusters using K-Means. Then, it identifies anomalies in those clusters using the Variational Bayesian Gaussian Mixture model. The model has been tested against the CICIDS 2017 dataset that contains new relevant attacks and realistic normal traffic, with a reasonable size. To balance the data, undersampling techniques were used. Furthermore, the features were reduced from 78 to 28 using feature selection and feature extraction methods. The proposed model shows promising results when identifying whether a data point is an attack or not with an F1 score of up to 91%.

1 INTRODUCTION

During the past decade, Machine Learning (ML) technologies have gained an expanding interest, enabling automation, accurate predictions and classification results from complex models, that are made possible and more efficient thanks to advanced processing resources (Zhavoronkov et al., 2018). From this perspective, various research works started to investigate the implementation of ML for diverse tasks such as malware analysis, intrusion detection, log analysis, threat classification, etc., in order to enhance the security by design principle in next-generation networks. The intersection between ML and cybersecurity has been studied for more than three decades, and both domains are recently experiencing a blooming stage due to the increasing deployment of next-generation networks in the society. ML, on the one hand, offers important capabilities to analyse threats and attacks in various network systems, enabling comprehensive and in-depth defense strategies. However, ML algorithms are raising several questions regarding their effectiveness in real-world scenarios. For instance, the lack of interpretability of many learning models makes it hard to develop defensive mechanisms against sophisticated attacks.

Cybersecurity, on the other hand, provides the means to protect data from intrusions or attacks that usually lead to high economic losses, personal information leaks and reduced quality and productivity of organisations. Intrusion Detection Systems (IDSs) are efficient counter-measures for detecting inappropriate use of host machines or networks and providing information security. IDSs monitor and analyse events to detect any deviations from a regular behaviour.

Several machine learning methods have been implemented to decrease the false positive rate of anomaly-based IDSs, including Extreme Learning Machine (ELM) (Singh et al., 2015) and Support Vector Machine (SVM) (Feng et al., 2014; **?**; **?**). However, most of these approaches only use supervised learning algorithms that strongly rely on the accurate labeling of the training dataset and are tested against outdated datasets.

This paper investigates the application of ML algorithms in Intrusion Detection Systems (IDSs) and provides a detailed evaluation of existing ML methods and their applications to different network systems. It proposes a new ML-based IDS model that relies on a hybrid approach that uses supervised and unsupervised algorithms to efficiently detect complex and sophisticated attacks (e.g., known and unknown). The proposed model first classifies the input data into various clusters using K-Means. Then, it identifies anomalies in those clusters using the Variational Bayesian Gaussian Mixture model. Conducted experiments show promising results reaching 91% of F1-scores in the supervised classification and up to 86% in the unsupervised classification.

The remainder of this paper is as follows. Section 2 describes the proposed model and discusses the core processing blocks. Section 3 details our methodol-

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ogy, including selected data-sets, different types of data pre-processing and selection techniques. Section 4 presents preliminary experimental results, before concluding in Section 5.

2 PROPOSED SOLUTION: HYBRID AI-BASED MODEL FOR IDS

The proposed solution introduces a novel ML based IDS model that relies on a combination between supervised and unsupervised learning in order to efficiently detect complex and sophisticated attacks, as depicted in Figure 1. Indeed, an unsupervised clustering algorithm, i.e., K-means, will first separate into clusters normal and abnormal behaviours. K-means is chosen because it ensures a low computation overhead. Second, the identified clusters will be labelled, by considering the location of the majority of the points in each cluster. Then, the boundary's/thresholds for each of those datasets will be set using the Variational Bayesian Gaussian Mixture model. All of the points that have a probability of belonging to a cluster smaller than the threshold will be classified as potential new and unknown attacks. Finally,all the points clustered as attacks by K-means will be processed using a supervised algorithm to be classified into different attacks. data that are classified as normal by K-Means will keep this classification.

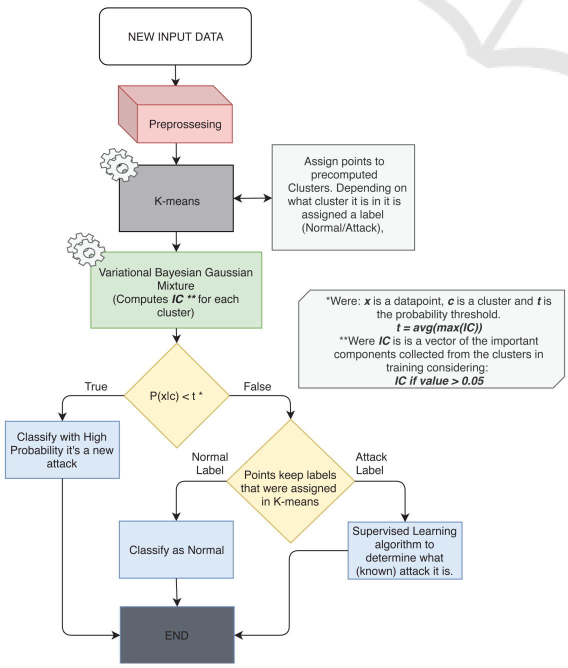


Figure 1: High Level Description of Proposed Method.

2.1 Training

After the preprocessing, the data goes through the K-Means algorithm which separates all the data points into clusters. Then, these clusters are labelled with respect to the majority of the classes they are compromised from (i.e., Normal or Attack). Next, the Variational Bayesian Gaussian Mixture method, as depicted in Figure 1, disregards non-important clusters by giving them a weight close to zero and so not all clusters will be considered. Note that a threshold can be set to select only significant clusters. Given that the limit is set, a vector will be returned by the model containing all the important components IC for each point in a cluster. Lastly for each of the clusters a threshold is computed as $t = avg(max(IC))$, where IC is the important components vector and the resulting t is the probability threshold for one cluster. Once these thresholds for all clusters are set the training phase is over.

2.2 Prediction

After preprocessing, the prediction data are given as inputs to the K-Means algorithm. As such, the data points will be assigned to their respected clusters. Just like in training, these clusters will be passed on to the Variational Bayesian Gaussian Mixture which will return the important components of each point. Then the $max(IC)$ for each point of the cluster will be calculated. It corresponds to the probability that the point belongs really to the cluster assigned by the K-Means. This probability is formulated as $P(x|c) = max(IC)$, where x is a data point, c is a cluster and IC is the important components vector of that datapoint. Lastly, once this is calculated the following expression will be executed to see if the point belongs to the cluster, $P(x|c) < t$. That is, if the probability that the point belongs to the given cluster assigned by K-means is lower than the threshold for that cluster which was set in the training phase, then it will be classified as new/unknown attack.

3 VALIDATION METHODOLOGY

3.1 Selected Datasets

Two publicly available datasets for intrusion detection systems have been studied and compared: (i) NSL-KDD[1] thanks to its large use in previous works for

[1] https://www.unb.ca/cic/datasets/nsl.html

fair comparison with other works; and (ii) CICIDS-2017[2] one of the newest publicly available datasets. CICIDS is more interesting than NSL-KDD as it contains samples inspired from real world examples, and it covers all criteria for building a reliable benchmark dataset as described by Gharib et al. (Gharib et al., 2016).

The NSL-KDD dataset is a modified version of the KDD CUP 99 dataset. It claims to solve some of the core problems of the of the previously widely used KDD CUP 99 dataset by removing the redundant records. As such, the classifiers will not be biased towards more frequent records. Attacks in this dataset fall into 4 distinct categories: Denial of Service Attack (DoS), User to Root Attack (U2R), Remote to Local Attack (R2L), and Probing Attack (Probe).

The CICIDS-2017 consists of 14 different attacks grouped into 9 categories: Brute Force FTP, Brute Force SSH, DoS, Heartbleed, Web Attack, Infiltration, PortScan, Botnet and DDoS. All of which are realistic and very common attacks. In addition it consists of 80 features, extracted using the CICFlowMeter[3]. Moreover, this dataset was built with the top priority of generating realistic background traffic. This was achieved using a proposed B-Profile system (Sharafaldin et al., 2018) profiling human interaction abstract behaviour and generating naturalistic, benign background traffic.

3.2 Imbalanced Datasets

The NSL-KDD dataset is class balanced with 52 percent of normal labels and 48 percent of attack labels. However, the distribution of attacks in the 4 categories is uneven, with *DoS* attacks having the biggest weight in the dataset and the *U2R* attack count being very small. This can potentially bias the model. To fix this issue, it is recommended to add new attack labels in the dataset to balance it better, since a resampling technique would result in redundant records.

The distribution of the normal and attack labels in the CICIDS-2017 dataset is uneven with 80 percent of normal labels vs 20 percent of attack labels. Even though the dataset is imbalanced, it is more realistic, since in the real world, we do not get as many instances of attacks as we get of normal network traffic. For these experiments, we used a random undersampling technique to balance this large dataset.

[2]https://www.unb.ca/cic/datasets/ids-2017.html

[3]https://pypi.org/project/cicflowmeter/

3.3 Classification Algorithms

The first algorithm of our proposed approach deals with unsupervised learning problem. In this case, K-means seems to be the best fit thanks to its simplicity and speed at which the predictions are generated. It is crucial to have a fast prediction time when implementing intrusion detection systems. Furthermore, algorithms like Density-Based Spatial Clustering of Applications with Noise (DBSCAN) tend to leave outliers out of the clusters and this is not optimal for these kind of systems since those outliers could be a minority of attacks. The second algorithm of our proposed approach is used to detect anomalies in clusters. The Variational Bayesian Gaussian Mixture is the selected algorithm because there is a smaller chance to end up in a local minimum considering that we only need to specify the maximum number of clusters to build the model, the algorithm will then find the actual number of clusters and set the weight of non-relevant clusters very close to zero (Nasios and Bors, 2006).

3.4 Performance Metrics

This section describes our evaluation metrics:

- **Accuracy:** It refers to the ratio of correctly predicted observations divided by the number of all observations, as $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
- **Precision:** It refers to the ratio of positively predicted observations divided by the total positive observations predicted as $Precision = \frac{TP}{TP+FP}$. High precision refers to the small false positive rate.
- **Recall:** It refers to the proportion of correctly predicted positive observations divided by all observations in a positive class, as $Recall = \frac{TP}{TP+FN}$.
- **F1 Score:** It refers to the weighted average of Precision and Recall, as $F1 = \frac{2 \cdot precision \cdot recall}{precision+recall}$. This rating brings into consideration both false positives and false negatives. F1 Score is the most suitable metric to find an equilibrium between Precision and Recall in a problem with irregular distribution.

3.5 Implementation

The proposed model is implemented using `Python`. The main libraries used for this model includes `pandas`[4], and `Scikit-Learn`[5]. As depicted in Figure 2, the initial step in the implementation process

[4]https://pandas.pydata.org/

[5]https://scikit-learn.org/stable/

is to import the data. For this implementation, we have selected the CICIDS 2017 dataset, which has been preprocessed, cleaned and balanced before splitting it in two main groups: (i) instances containing only normal activities, and instances containing attacks (e.g., Bot, Heartnleed, DoS Slowhttptest). 80% of the dataset has been used for training and the remainging 20% were used for testing. The training dataset is further split into two subsets: (i) the training subset, containing 80% of the selected training instances, (ii) the validation subset, containing 20% of the selected training instances. The validation serves to evaluate the model with different configurations during pre-production.

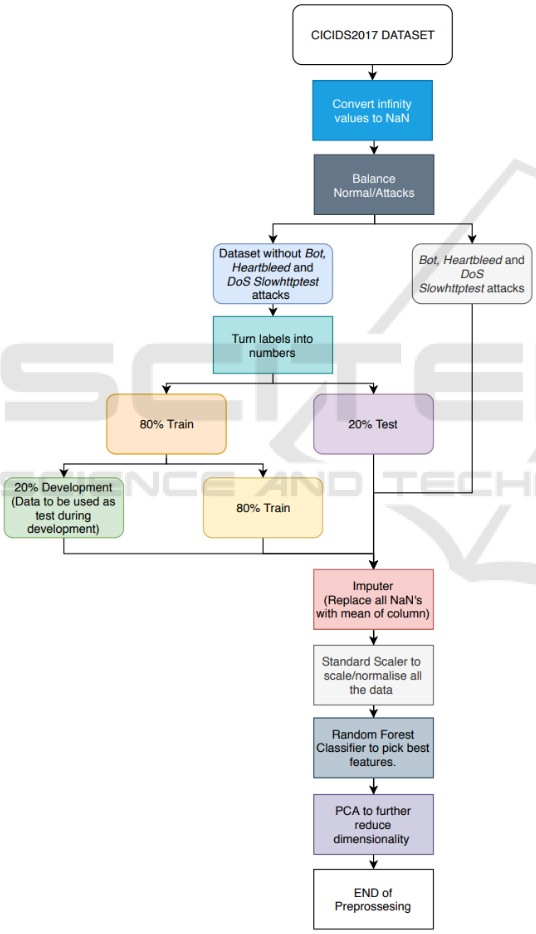


Figure 2: Preprocessing flowchart.

Once the dataset is split, all `NaN` values were replaced by the mean values of each column. After this process, data standardisation was performed by using the `StandardScaler` process from the `Scikit-Learn` library. Next step is feature selection. To carry out this task, the `random forest classifier` from the `Scikit-Learn` library was used. It was trained with the train dataset and with the hyperparameters of `n_estimators = 100` and `max_depth = 2` all the others were set to default. For the test set, only 49 out of the total of 78 features are considered as important. Therefore, all the features were chosen to build the models. As a feature extraction method, Principal Component Analysis (PCA) was used to fit the training data to avoid bias. The hyperparameters used were: `n_componets = number of features` (49 as taken from the feature selection), `svd_solver = 'randomized'` and `iterated_power = 30`. The last step in the preprossesing is to decide how many of PCA components are kept by computing and plotting the PCA variances for all clusters. Considering that after 28 features, the variances do not change, the hyperparameters chosen for the PCA algorithm are `n_components = 28`, and `max_iter = 200`.

The implementation of our proposed model considers implementing K-Means and the Variational Bayesian Gaussian Mixture algorithms.

3.5.1 K-Means

During K-Means implementation for clustering data, we tried two methods for fixing the cluster numbers (i) the elbow method and (ii) the cross validation with PCA using the development dataset so that the inertia converges. Inertia is the sum of squared distances of samples to their closest cluster centre. Unfortunately, when testing with the development set none of them yielded high accuracy results. Therefore, we tested all the accuracy's on the training and development tests starting with 2 clusters until reaching 50 clusters. We then picked the number of clusters with the highest accuracy. As shown in Figure 3, 46 clusters provide the highest accuracy level (i.e., 91% of accuracy). All the tests are done in 200 iterations. It is worth noting that both development and train sets have almost equal accuracy levels.

To calculate the accuracy of the model, the number of points belonging to each label (Normal or Attack), was measured and the cluster was assigned the label of the class it had the majority of samples in, since we actually had labelled data.

3.5.2 Variational Bayesian Gaussian Mixture

Bayesian Gaussian Mixture models were used to calculate the probability of a point belonging to the cluster. As stated in the aforementioned sections, the algorithm returns the probability of a point belonging to any of the clusters, these numbers are called components. Since they are probabilities, their sum is one, this means for this approach to work we must take

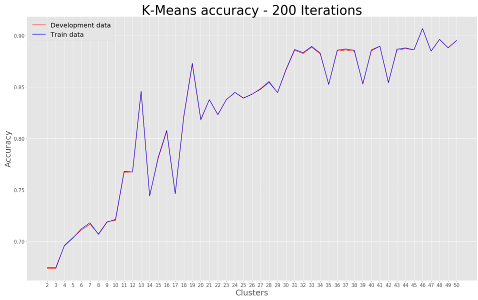


Figure 3: K-Means accuracy plot.

a look at only the important components. We set a threshold to 0.05 after testing with the train and validation sets. The algorithm takes only the components that are equal to or bigger than the threshold for each of the training clusters. Then, the validation set is used to predict the probability of the points belonging to each of those clusters. Once done, only the biggest of those components is taken for each point in the cluster and as a last step they are averaged (as discussed in section 2.1).

4 IMPLEMENTATION RESULTS

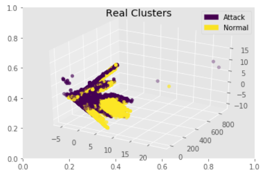
4.1 Clusters' Visualization

Figure 4(a) depicts the actual clusters with the real labels of the test data that are used for evaluation purposes. Let us recall that a model is considered as perfect if it is able to predict exact same clusters. Figure 4(b) shows the clusters that are predicted through the different conducted experiments. We note that the test set does not contain any new attacks. If we look closely at Figure 4, we notice that there exist some minor points which are wrongly classified.

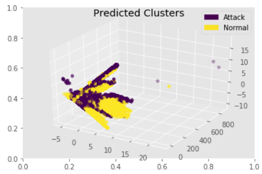
In order to evaluate the classification capabilities of the proposed methodology, we considered a single set composed by the concatenation of the test set and the set of new attacks, as shown in Figure 4(c). The resulting clusters belong to both known and unknown attacks. We note that in Figure 4(c), there is a whole new "line" in purple. The data points in this line belong to the new attacks that were not present during the training of the model. These are the data points that our solution aims at detecting and classifying.

4.2 Evaluation Results

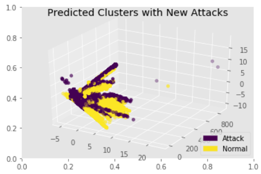
This section details the evaluation results of the proposed model with different configurations and discusses the computation overheads.



(a) Real Clusters



(b) Predicted Clusters



(c) Predicted Clusters with New Attacks

Figure 4: Real vs Predicted Clusters.

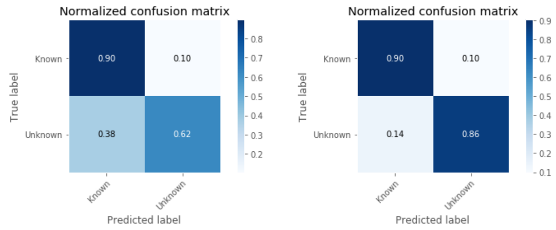
Table 1: Normal / Attack Detection with 45 and 46 Clusters Evaluation Results.

No of Clusters	45	46
F1 score	89%	91%
Recall	94%	95%
Precision	85%	88%
Accuracy	89%	91%

4.2.1 Evaluation with 46 Clusters

The first configuration considers 46 clusters. It was evaluated with respect to the selected metrics, as detailed in section 3.4. For the K-Means algorithm, we used the test set, to estimate the number of both attacks and normal data points that are correctly predicted. The F1 score was 0.91% while the Recall score 0.95%. Furthermore, the precision score was 0.88% and the accuracy score was 0.91% as shown in Table 1.

To evaluate the capacity of the Variational Bayesian Gaussian Mixture for efficiently detecting new attacks, we first implemented the prediction pipeline with the test set. Then, we assessed the pipeline algorithms using the attacks' dataset. Afterwards, both predictions are concatenated into one data-frame and evaluated. This concatenation permits to identify the real labels and evaluate the results accordingly, since all of the datapoints in the unknown attacks should be set to unknown and all the datapoints in the test set to known. The results of this evaluation are depicted in 5(a). The results are shown in a normalised confusion matrix in order to provide human-centric accurate results. From Figure 5(a), we deduce that the results of our evaluation with 46 clusters are fairly good, 62% of the unknown labels are correctly predicted.



(a) Confusion matrix (46 clusters) (b) Confusion matrix (45 clusters)

Figure 5: Comparison of Confusion Matrix results obtained for the different clusters.

4.2.2 Evaluation with 45 Clusters

As detailed in section 4.2.1, we conduct the same evaluation pipeline while considering 45 clusters, in order to assess their impacts on the prediction accuracy. In fact, we assumed that the obtained results with 46, even though considered as good, may be improved. For this purpose, we conduced a trial with less clusters and evaluated the different metrics. This second configuration, i.e., 45 clusters resulted in an improved accuracy in predicting unknown attacks compared to the first setting. However, it negatively impacted the evaluation of K-Means. The F1 score dropped down to 0.89% and the Recall score to 0.94%. Furthermore, the Precision score stepped down to 0.85% and the total accuracy score to 0.89%.

4.3 Discussion

Figure 4(a) presents a common illustration of the real attack and normal clusters. It is difficult to distinguish one cluster from the other one since they are merged. This is mainly due to the close behaviour between a normal and an attack event. In our conducted experiments, two configurations are evaluated, one using 45 and another using 46 clusters. This latter showed better results using the validation dataset, thanks to the similar behaviour of normal and attack events. Given that, the selected criteria to identify if a cluster is normal or malicious is the class of the majority of events, a higher number of clusters broke down the events in a way that could improve the classification accuracy of the clusters.

The number of clusters to use resolves the tradeoff between the accuracy to detect normal/attack events and the good performance of the model to classify known/unknown ones. Thus, based on each setting's requirements, i.e., to classify or detect known/unknown attacks, our results showed that it is more convenient to use the model with 45 clusters for classification and 46 clusters for detection. Moreover, in both cases, the accuracy to classify normal/attack events is still high (at least 89%).

The precision and recall scores for the model using 45 clusters are fairly high. The precision metric indicates that 85% of the events classified by the model as attacks, are correct, meaning that the model has a small false positive rate. The recall metric indicates that 94% of the real attacks are correctly predicted. The F1 score (or the weighted average of precision and recall) was equal to 89%. This metric shows that the general detection rate of the combined models is good. The confusion matrix is helpful to analyse the known/unknown predictions of the models. The model using 45 clusters was the best model since only 0.1% percent of the known events were misclassified as unknown, and only 0.14% of the unknown events were misclassified as known.

The model using 46 clusters obtained the same results as the model using 45 clusters when predicting the known events. This shows that the difficulty in the model lies in detecting the unknown attacks. Using 46 clusters, the model misclassified 38% of the unknown events, which are 24% more than the model using 45 clusters.

5 CONCLUSION

This paper presented a hybrid approach to tackle the problem of implementing intrusion detection systems using machine learning models. The CICIDS 2017 dataset has been chosen, since it contains new relevant attacks and realistic normal traffic, with a reasonable size. The normal and attack data points were unbalanced, to balance the data undersampling technique was used.

The highest performance for the K-Means clustering was obtained with 46 clusters. The F1 score was 0.91% while the Recall score 0.95% the Precision score was 0.88% and the Accuracy score was 0.91%. The highest performance for the Variational Bayesian Gaussian Mixture model was obtained with 45 clusters at 90% of the known attacks predicted as known and 86% of the unknown predicted as unknown.

Future work will concentrate on evaluating other ML models and integrating the proposed solution into a SIEM system in a dynamic setting. This will demonstrate the versatility of the proposed methodology in ever-evolving environments. In addition, we will investigate the use of fully homomorphic encryption as discussed by (Sgaglione et al., 2019; Boudguiga et al., 2020) to make the intrusion detection more privacy-preserving. However, using homomorphic encryption will require the adaptation of the used models and may result in a loss of accuracy.

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